A MACHINE LEARNING MODEL FOR SOLAR SAIL SHAPE RECONSTRUCTION USING FLIGHT DATA

Ryan H. Wu,[*] Sanjog Gururaj,[†] and Daniel A. Tyler[‡]

Solar sail deformation leads to disturbance torques from solar radiation pressure, driving performance requirements for momentum management systems. For the Solar Cruiser technology demonstrator mission, we have developed a model leveraging neural network-based machine learning to derive sail shape characteristics. The model uses torque and attitude telemetry simulated from a reduced-order tensor model of the deformed sail mesh over a characterization sequence. The machine learning model predicts sail boom deflection with comparable accuracy to that of an onboard context camera. This model can discover sail shape with no additional mass or data downlink requirements, allowing for validation of sail force modeling assumptions using in flight data. The results from the project hold promise for the further implementation of machine learning techniques in solar sail telemetry analysis and control.

INTRODUCTION

Solar Cruiser Mission Design

The Solar Cruiser mission aims to demonstrate solar sail propulsion technology to enable heliophysics science missions up to and including high solar inclination orbits, sub-L1 halo orbits, and non-Keplerian solar and other planetary body orbits using a 1653 m^2 solar sail (Figure 1).[1] The craft consists of four booms with four sail quadrants attached at the distal ends of the booms, and connected to each other via a catenary near the roots of the booms. Nominally, the sail will demonstrate station-keeping sunward of the Sun-Earth L1 point and transfer outside of the ecliptic plane via increasing heliocentric inclination. The sail aims to demonstrate propulsion, pointing, and momentum management capabilities of sail technology to allow for future heliophysics science payloads. The success of Solar Cruiser would enable new missions with otherwise restrictive Δv stationkeeping requirements, including observations at high inclination solar orbits, space weather monitoring with increased warning times, and other solar sail mission applications for exploration.

Sail Shape Requirement

For the sailcraft, a detailed understanding of the sail shape is necessary to both accomplish mission objectives and mature our understanding of solar sail behavior for future science missions.[2] Due to the lightweight and flexible materials and much larger size compared to other spacecraft,

*Undergraduate Student, Mechanical Engineering, Columbia University, 220 S. W. Mudd Building, 500 West 120th Street, New York, NY 10027. Work completed as part of NASA MSFC Internship.
†Undergraduate Student, Computer Science, University of Arkansas, 1 University of Arkansas, Fayetteville, AR 72701. Work completed as part of NASA Pathways Internship.
‡Guidance Navigation and Control Engineer, NASA Marshall Space Flight Center, Martin Rd SW, Huntsville, AL 35808.

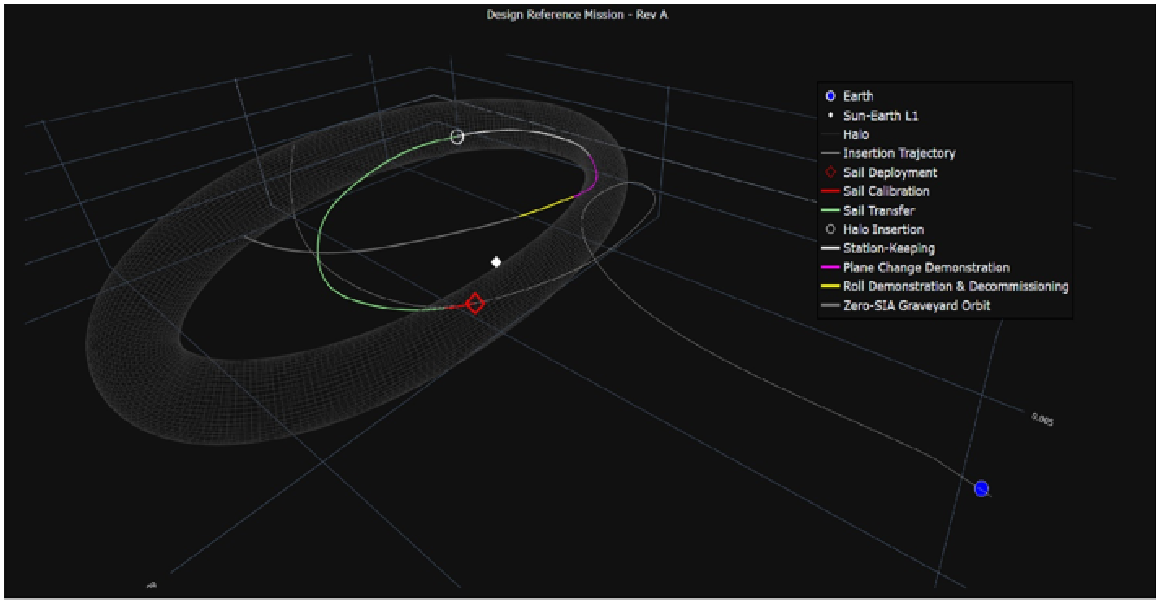


Figure 1: Mission trajectory for Solar Cruiser.

solar sail deflection due to manufacturing defects, thermal stresses, tension, and other factors become drivers of attitude control design considerations. In solar sails and other low thrust systems, performance is particularly sensitive to mass.[3] Consequently, the sizing, and thereby mass, of attitude control and momentum management systems, such as reaction wheels, needed to mitigate deflection-induced disturbance torques limit the characteristic acceleration a_c. This constricts the station keeping and orbital maneuvering capabilities, such as the distance from the sun maintained in a sub-L1 artificial halo orbit. As such, understanding sail shape characteristics both before launch and during mission operations is critical for validating sail shape models to inform requirements and mission design, as well as predicting torques at riskier attitudes with high sun incidence angles (SIAs) to update mission constraints based on *in situ* capabilities.

However, characterizing the sail shape becomes a challenge once the sail is in flight, as instrumentation to quantify boom deflection and similar shape parameters leads to additional mission cost and mass, further limiting propulsion performance. For Solar Cruiser, the baseline solution is a context camera which is able to see one sail quadrant and two booms, providing 3.81 cm resolution at the boom tips to identify deflection. This method faces several limitations, including the fact that not all booms and quadrants can be observed, as well as difficulties in scaling to a future science mission with a larger sail and longer booms. The potential for indirect system observations without the parasitic mass of a context camera would thus provide additional insight to mission planners during operation for a broader range of missions.

Sail Shape Modeling

Due to the lightweight and flexible nature of solar sail materials, deflections and distortions become drivers of performance considerations, and thus need to be realized in detail. As the boom structures are designed to be lightweight for structural stability in zero gravity conditions, testing of sail deployment on Earth is difficult due to gravity offload requirements, which also creates challenges for shape modeling. Prior work has focused on quantifying theoretical solar sail deflection

using finite-element analysis or Euler-Bernoulli beam theory, which provide nominal values for sail deflection under ideal loading conditions.[4] Such analysis could then be used to drive momentum management and control requirements, and optimize attitude control parameters.[5] Particularly with Solar Cruiser's objective as a technology demonstration mission, verifying these sail shape modeling assumptions will be an important component of maturing the technology and preparing for missions which continue to expand sail size and capabilities.

Machine Learning for Control

Machine learning (ML) methods use data-driven techniques to construct and improve computational models for regression, optimization, and classification. Within guidance and control, ML has been applied to problems such as spacecraft telemetry analysis, trajectory optimization, and fault diagnosis.[6,7] Specifically, deep neural networks, an ML technique which applies nonlinear activation functions to linear combinations of inputs with a set of weights and biases, are universal function approximators, making them useful as closure functions for modeling applications.[8] These neural networks are thus able to represent highly nonlinear systems with complex dependencies and underlying physics, and have been used in sailcraft control to represent modeling uncertainty and transfer trajectory components.[5,9]

For the application on the Solar Cruiser mission, we propose a machine learning-driven tool to derive sail shape from existing telemetry. We aim to apply ML techniques to the inverse problem of determining sail shape from sail attitude and torques, both of which would be present in telemetry data already being provided by the spacecraft in flight. Thus, the model could potentially supplement or reduce the scope of the onboard context camera while allowing for the possibility of sail characterization without the need for physical instruments on future sail missions.

METHODS

Characterization Concept of Operations

In the Solar Cruiser mission Concept of Operations, the proposed sail characterization period would consist of a series of slews through a range of sun incidence angles (SIAs) and clock angles (Figure 2). SIA is defined as the half-cone angle of the sun with respect to the sail normal vector, and clock angle is defined as the rotation of the sail body about that normal vector. The sail coordinate system is defined where SIA and clock are the 2nd and 3rd, respectively, angles of a Z-Y-Z (roll-SIA-clock) Euler rotation sequence, where Z is the normal vector of the sun-facing side of the sail and Y is pointed normal to the ecliptic plane, in the direction of the angular velocity vector of the Earth's orbit around the Sun, when the roll angle is 0°. The proposed characterization sequence would encompass a full range of clock angles at an intermediate SIA, as well as shorter 30° slews around the predicted best and worst disturbance torque SIAs. Throughout this characterization sequence, disturbance torques recorded by the attitude determination and control system will be used to evaluate sail shape in the machine learning prediction model.

Shape File Generation

Shape file generation for the sail dataset begins with an ideal, flat sail, parameterized as a mesh model. The sail is then deformed according to the variables outlined in Table 1, reflecting variability in thermal stresses, manufacturing defects, and tension (Figure 3). Out-of-plane deflection magnitudes at the tips of the booms are introduced in the nominal value, as well as uncertainty terms due

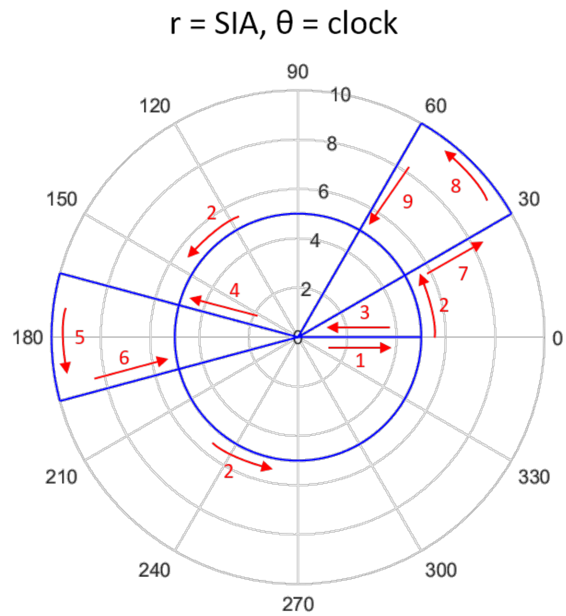


Figure 2: Sail characterization concept of operations for Solar Cruiser. The blue line indicates the direction of the sun relative to the sail normal vector (center of the diagram) during the slews (arrows).

to the aforementioned influences. Maximum out-of-plane deflection magnitudes in the sail membranes are also introduced, and the center of mass within the sail plane of the overall spacecraft is varied to reflect asymmetries in final assembly. Finally, the deflection direction along the sail normal axis of each one of the four booms and membranes is varied independently. The final dataset comprises 1.1 million sail shapes, containing all permutations of the provided shape metrics.

Table 1: Sail Shape Variables

Sail Shape Variable	Number of Cases
Nominal Boom Tip Deflection	11
Error Boom Tip Deflection	5
Error Membrane Deflection	6
X/Y Center of Mass Offset	7
Boom Tip Deflection Direction	8
Membrane Deflection Direction	8

Sail Torque Model

The shape file is then parameterized via the Rios-Reyes reduced order model of characteristic tensors for efficient downstream computational processing.[10] These tensors are independent of the properties of the incident light, and consist of integrals over the normal vectors of each mesh element to compute the net force and moment applied on the sail due to the aggregate effect of all elements as a function of the angle of incident light. Sail reflectivity ρ and absorptivity a are assumed to be constant over the surface of the sail irrespective of SIA. The tensor model equation for force is

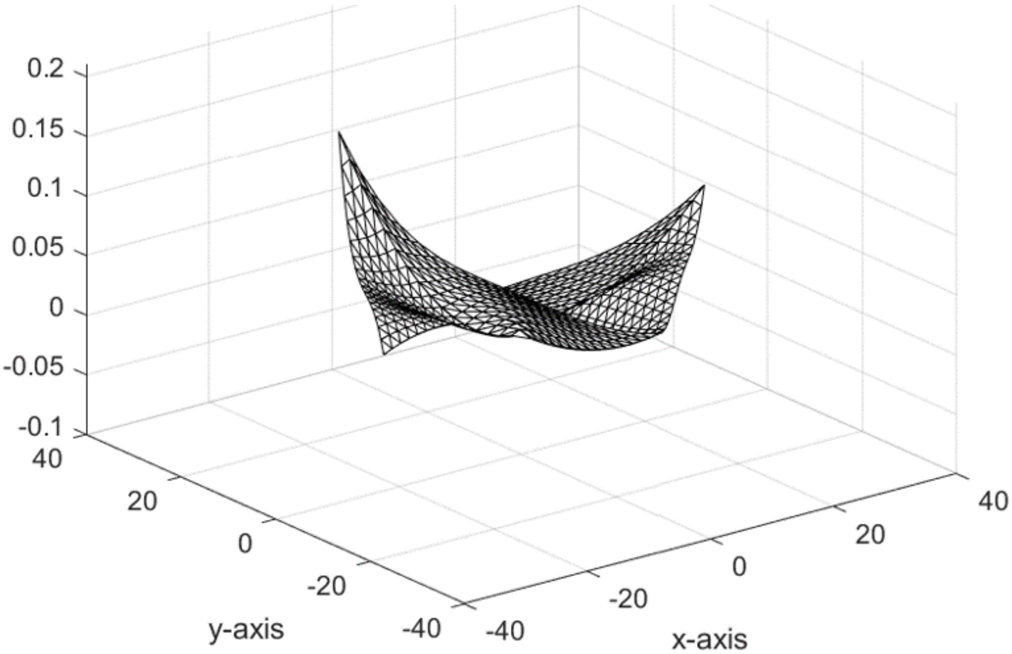


Figure 3: Example of a deflected sail mesh.

as follows, where a_n are variables derived from optical sail properties and $P(r)$ is defined as the radiation pressure at distance r from the sun.[10]

First, the tensors $\boldsymbol{K}^m$ and $\boldsymbol{L}$ are found from the surface normal integrals over the sail mesh:

$$\boldsymbol{K}^m = \int_A \tilde{\boldsymbol{r}} \cdot \hat{\boldsymbol{n}}^m dA \tag{1}$$

$$\boldsymbol{L} = \int_A \hat{\boldsymbol{n}}\boldsymbol{r} dA \tag{2}$$

$\tilde{\boldsymbol{r}}$ is a dyad defined such that $\boldsymbol{r} \times d\boldsymbol{F} = \tilde{\boldsymbol{r}} \cdot d\boldsymbol{F}$. Provided the sun position unit vector $\hat{\boldsymbol{r}}_0$ pointing from the sun to the sail in the reference frame of the latter, the total solar force and moment vectors can be found in a highly computationally efficient manner.

$$\boldsymbol{M} = P(r)[a_2\boldsymbol{K}^2 \cdot \hat{\boldsymbol{r}}_0 - 2\rho s\hat{\boldsymbol{r}}_0 \cdot (\boldsymbol{K}^3 \cdot \hat{\boldsymbol{r}}_0) - a_3\hat{\boldsymbol{r}}_0 \cdot \boldsymbol{L} \cdot \tilde{\hat{\boldsymbol{r}}}_0] \tag{3}$$

This numerical integration is performed for each of the generated sail shape files to create the characteristic tensors for each sail shape. Using the SIA and clock angle attitudes of the aforementioned characterization sequence laid out in the Concept of Operations, sun normal vectors are identified at a resolution of 1° in SIA and 30° in clock angle. The resolution is constrained by the processing power and memory available, and a future deployment of a similar modeling strategy may benefit from increases in attitude resolution. With the permutations in shape tensors and attitudes, a total of 100 million force and torque vectors are computed.

Neural Network Architecture

The table of shape parameters, attitudes, and torques is then split into training and evaluation datasets for the neural networks, with a division of 70% training and 30% evaluation data. All data is normalized to unity standard deviation and centered to ensure training stability, which will be reversed when extracting regression results. The networks consist of densely-connected feed-forward regression networks which are trained on a single sail shape metric (eg. boom deflection on the +X boom). The model consists of two components, a regressor network which finds a best fit shape metric provided the torque vector at a single attitude, and a stacker network which creates an ensemble model from the regressor predictions at all the attitudes within the sail characterization slews (Figure 4). A preliminary hyperparameter optimization study is conducted to prevent overfitting in the model using the withheld evaluation dataset, and model convergence in all training is also assessed using the latter dataset. The final model architecture used for each of the regressor and stacker networks is described in Table 2. The activation function used was the Scaled Exponential Linear Unit, which has self-normalizing properties which reduce instabilities in the backpropagation process due to exploding or vanishing gradients.[11] Kaiming Normal initialization and the Adam optimization algorithm are used in the training process for the networks, with the loss function defined as Mean Squared Error. This network architecture is first used in the regressor network to provide a best prediction of the targeted shape metric at a given SIA and clock angle combination within the characterization sequence.

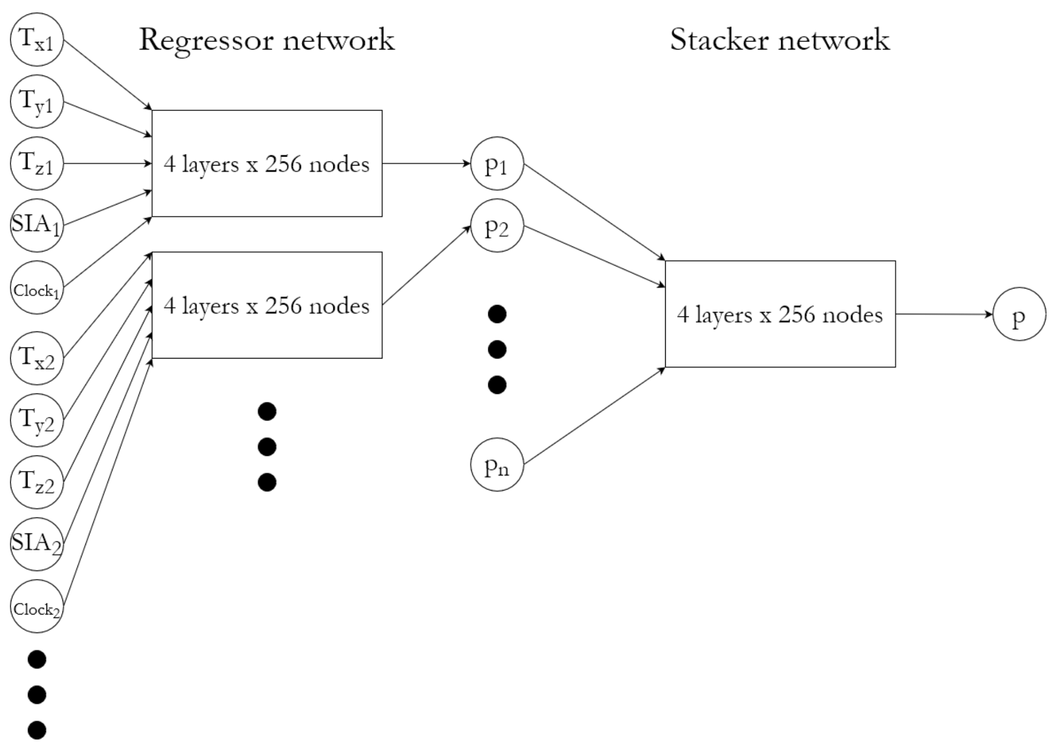


Figure 4: The neural net model structure used. The torque vector and attitude are input to a regressor network, whose results for the shape parameter p are then combined in an ensemble model by the stacker network.

However, as certain points within the characterization sequence provide very low disturbance

Table 2: Neural Network Architecture Parameters

	Regressor Network	Stacker Network
Layers	4	4
Nodes per Layer	256	256
Learning Rate	$5 * 10^{-4}$	$1 * 10^{-3}$
Batch Size	2048	256
Training Epochs	10	500

torque magnitudes, such as low-SIA observations, we hypothesize that the regressor may face inherent limitations on performance at these attitudes due to potential degeneracies between various sail shapes producing near-identical torques. To distinguish shapes in these situations, an additional stacker network is used to ensemble the regressor predictions at all points within the characterization sequence to find a most likely shape provided disturbance torques from the entire sequence. This network takes the shape metric predictions from each attitude provided by the regressor model as an input, and yields a single, more accurate prediction of the shape metric using the ensemble model.

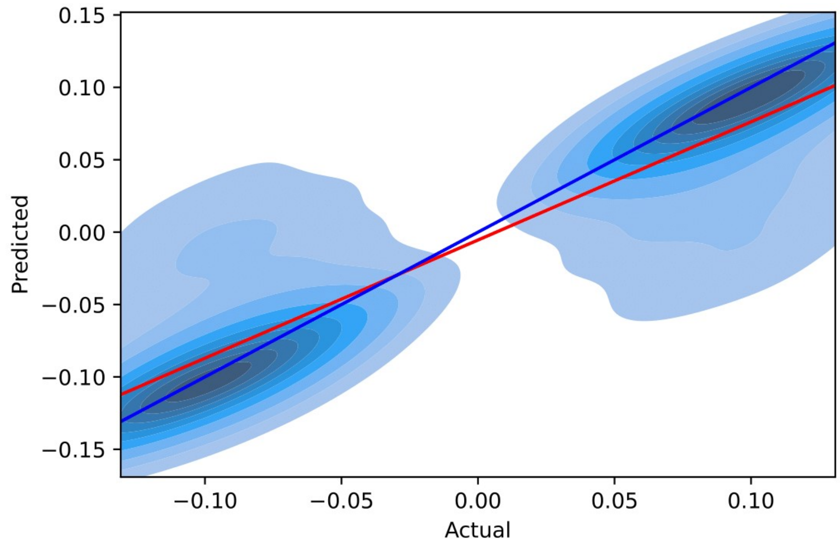
RESULTS

The network is evaluated using boom deflection for a single boom, though preliminary training data show equivalent correlations at the other booms and with other shape metrics. The regressor network alone is able to fit boom deflection with a 3σ error of 7.5 cm, with the majority of the data being strongly correlated and a notable amount of outliers, potentially from the previously hypothesized degeneracies (Figure 5a). σ is defined as the standard deviation for a normal distribution of the error between the neural net prediction and the ground truth shape model. However, with a mean deflection magnitude of 9.6 cm in the dataset, the regressor performance alone is insufficient to characterize the shape of the sail. Particularly at the outlier points, it is possible that single measurements at low-torque attitudes will lead to incorrect predictions of shape metrics, thus warranting some form of filtering or weighting of the torques over the entire characterization sequence to find the best-fit shape metric value.

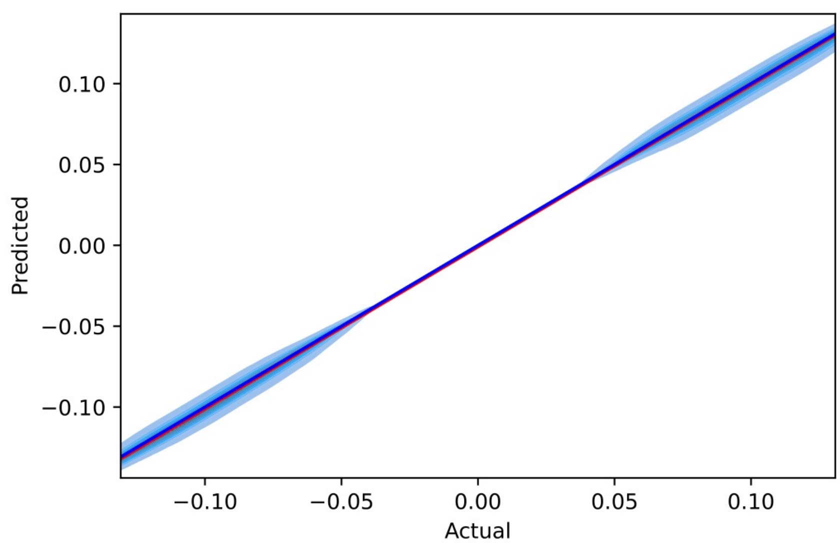
This weighting is performed by the stacker network, which performs significantly better after ensembling the regressor predictions. The network is able to predict the boom tip deflection to a 3σ error of 1.38 cm and a mean error of 3%, which is finer than the 3.81 cm resolution of the context camera requirement at the boom tips (Figure 5b). There are no visible outlier groups, and the network error does not scale with increasing deflection magnitude, indicating that the model does not saturate in extreme deflection cases (Figure 6). However, further testing of this model is still necessary to examine whether it is extensible to deflection magnitudes outside of the range tested. Nevertheless, we believe that the stacker network is able to mitigate the influence of outlier or degenerate cases within the attitudes of the sail characterization sequence. This yields a single, more accurate prediction of boom deflection, which can then be used for mission planning applications.

DISCUSSION

The ML model is capable of predicting boom deflection with a comparable accuracy to an onboard context camera, allowing for a potential scope reduction in the camera and further validation of the sail shape modeling assumptions using flight telemetry. The model is able to successfully



(a) Regressor network correlation (single attitude)



(b) Stacker network correlation (all attitudes in characterization sequence)

Figure 5: Density plots of correlation between actual and predicted boom deflection, in meters. The red line represents the best fit, while the blue line is a 1:1 correlation.

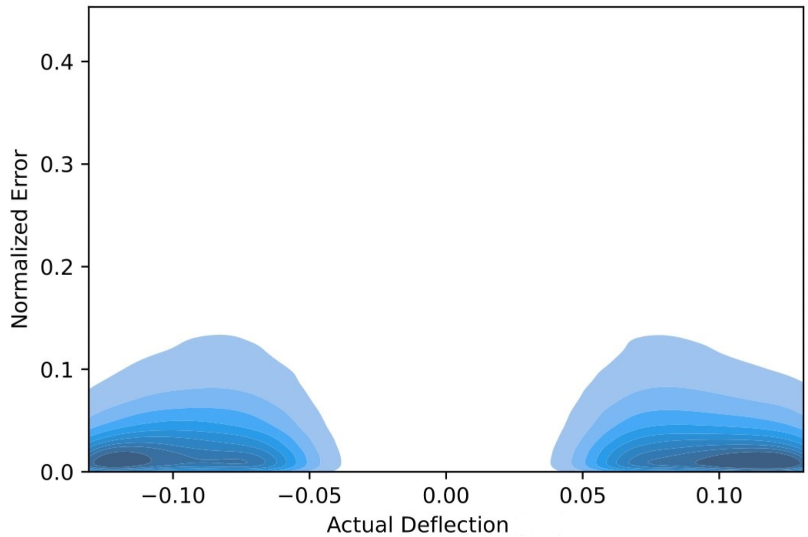


Figure 6: Density plot of stacker network error vs actual deflection in meters, normalized by boom deflection magnitude.

train using simulated torque and attitude telemetry without overfitting, and make predictions on boom deflection cases which it was not trained on to a high degree of accuracy. The performance of this model enables several additional applications both within the Solar Cruiser mission and in other sailcraft missions, as discussed below.

Combining the predicted sail characteristics from the model with the reduced-order tensor model used to generate the dataset, the neural network architecture could extrapolate torque predictions to new attitudes, allowing for mission operators to make informed decisions about operational constraints, such as maximum SIA, using information about the sail shape. These extrapolated predictions can be compared with ground truth flight data to evaluate the joint ML modeling and tensor model architecture. As this disturbance torque mesh and tensor model has not been tested in flight conditions, validating the modeling assumptions will reduce the inherent uncertainties carried forward by future solar sail missions using these techniques.

Specifically for the Solar Cruiser mission, the ensemble performance of the stacker network can be used to revise mission plans as well. Provided the weights from the stacker network, the sail characterization plan itself could be further optimized to reduce duration and slew performance requirements, since it is possible that a more limited ensembling at fewer attitudes could still be sufficient to derive comparable accuracy metrics for the sail shape. The knowledge of shape can be used to update mission plans to improve pointing performance and momentum management performance while in flight, for later components of the flight demonstration. For future missions, the relatively lightweight nature of the model also allows for integration into flight software to enable onboard autonomy, where the sail orients itself at angles which minimize disturbance torques using an internal model of its shape.

Future work on this model includes introducing noise into the attitude and torque measurements consistent with flight data to evaluate the model sensitivity to errors introduced within actual measurements. Due to black-box nature of neural networks, direct examination of the weights and biases is unable to yield information on model sensitivity and stability, and as such further verification is

necessary to ensure the system is able to make accurate predictions in spite of sensor limitations. For flight implementation, higher angular resolution attitude samples can be used to increase model fidelity, and a more extensive hyperparameter optimization process can be used to further improve fitting performance and complexity.

Nevertheless, the success of this model shows the potential for machine learning to play a role in solar sail telemetry analysis and fault diagnosis, particularly with guidance and control problems which require inverting known physical dynamics. Other upcoming solar sail missions such as Advanced Composite Solar Sail System (ACS3) could also benefit from this modeling strategy, as they can leverage preexisting telemetry data to make determinations of sail shape while in flight. We hope that this modeling strategy could serve as a useful tool for data-driven shape characterization in current and future solar sail missions, aiding in improving design of the solar sail technology system, especially the momentum management system, and mission design and operations without the need for dedicated sensors or data downlink.

CONCLUSION

In this project, we designed and implemented a machine learning model which derives sail shape from simulated telemetry for the Solar Cruiser mission. Due to the technology demonstration nature of the mission and the need to generate accurate disturbance torque predictions to derive momentum management system design, characterizing this sail shape is crucial for maturing our understanding of solar sail technology. As such, we created 1.1 million sample sail shapes deflected according to a range of shape metrics, which were then converted to reduced-order tensor models for torque calculation at a range of attitudes consistent with the characterization sequence for Solar Cruiser. Using a two-step neural network-based design which makes predictions at individual attitudes and then ensembles them across the characterization sequence, we demonstrated the ability of the model to predict boom deflection to an accuracy of 1.38 cm, exceeding the 3.81 cm resolution of the onboard camera. Further work is necessary with introducing realistic flight conditions in noise and resolution before this model can be implemented, but these results enable further validation of our shape and torque modeling approaches using inflight data, as well as help inform mission planning for Solar Cruiser and similar missions. The results also indicate the potential of machine learning strategies for telemetry analysis and fault diagnosis, hopefully enabling greater autonomy and situational awareness in future missions.

ACKNOWLEDGMENT

The authors thank the Solar Cruiser mission for funding the summer internship which produced this research, as well as the NASA Office of STEM Engagement for coordinating the internship. The authors also thank the contribution of members of the Solar Sail Attitude Determination and Control System team at NASA Marshall Space Flight Center and Redwire Corporation to the project in sail design, modeling, and simulation.

REFERENCES

[1] J. B. Pezent, R. Sood, A. Heaton, K. Miller, and L. Johnson, "Preliminary trajectory design for NASA's Solar Cruiser: A technology demonstration mission," *Acta Astronautica*, Vol. 183, June 2021, pp. 134–140, 10.1016/j.actaastro.2021.03.006.

[2] Z. Jin and W. Tianshu, "Coupled Attitude-Orbit Control of Flexible Solar Sail for Displaced Solar Orbit," *Journal of Spacecraft and Rockets*, Vol. 50, May 2013, pp. 675–685, 10.2514/1.A32369.

[3] L. Johnson, R. M. Young, and E. E. Montgomery IV, “Recent advances in solar sail propulsion systems at NASA,” *Acta Astronautica*, Vol. 61, June 2007, pp. 376–382, 10.1016/j.actaastro.2007.01.047.

[4] B. Taleghani, D. Sleight, D. Muheim, K. Belvin, and J. Wang, “Assessment of Analysis Approaches for Solar Sail Structural Response,” *39th AIAA/ASME/SAE/ASEE Joint Propulsion Conference and Exhibit*, Huntsville, Alabama, American Institute of Aeronautics and Astronautics, July 2003, 10.2514/6.2003-4796.

[5] O. Eldad, E. G. Lightsey, and C. Claudel, “Minimum-Time Attitude Control of Deformable Solar Sails with Model Uncertainty,” *Journal of Spacecraft and Rockets*, Vol. 54, July 2017, pp. 863–870, 10.2514/1.A33713.

[6] M. Shirobokov, S. Trofimov, and M. Ovchinnikov, “Survey of machine learning techniques in spacecraft control design,” *Acta Astronautica*, Vol. 186, Sept. 2021, pp. 87–97, 10.1016/j.actaastro.2021.05.018.

[7] J. R. Mansell and D. A. Spencer, “Deep Learning Fault Diagnosis for Spacecraft Attitude Determination and Control,” *Journal of Aerospace Information Systems*, Vol. 18, No. 3, 2021, pp. 102–115. Publisher: American Institute of Aeronautics and Astronautics _eprint: https://doi.org/10.2514/1.I010881, 10.2514/1.I010881.

[8] K. Hornik, M. Stinchcombe, and H. White, “Multilayer feedforward networks are universal approximators,” *Neural Networks*, Vol. 2, Jan. 1989, pp. 359–366, 10.1016/0893-6080(89)90020-8.

[9] Y. Song and S. Gong, “Solar-sail trajectory design for multiple near-Earth asteroid exploration based on deep neural networks,” *Aerospace Science and Technology*, Vol. 91, Aug. 2019, pp. 28–40, 10.1016/j.ast.2019.04.056.

[10] L. Rios-Reyes and D. J. Scheeres, “Generalized Model for Solar Sails,” *Journal of Spacecraft and Rockets*, Vol. 42, Jan. 2005, pp. 182–185, 10.2514/1.9054.

[11] G. Klambauer, T. Unterthiner, A. Mayr, and S. Hochreiter, “Self-Normalizing Neural Networks,” 2017. Publisher: arXiv Version Number: 5, 10.48550/ARXIV.1706.02515.